Evaluation of Latent Fingerprint Technologies: Fusion

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Introduction

• **Fusion:**
  - Consolidating information from multiple sources (e.g. multiple fingers, multiple algorithms).

• **Principle Goals:**
  - Improve identification rate.
  - Improve rank ordering to reduce workload on the human examiner.
Fusion Levels

- Fusion can occur at various stages during the matching process.

- In the diagram below, fusion occurs at the image level. Multiple latent images of the same finger are combined to create a new composite image.
Rank Level Fusion

- ELFT focused on fusion at the rank / score level, which occurs after invocation of the automated matcher(s).

- In the diagram below, the latent images are searched independently of each other. Their candidate lists are then “fused”.

[Diagram showing search and fusion process]
Rank and Score Level Fusion schemes

A candidate receives a rank and a score on each candidate list. These scores or ranks are fused to produce an overall score.

- **Sum Score:** \( s_{\text{fused}} = s_1 + s_2 + \ldots + s_n \)
- **Minimum Rank:** \( s_{\text{fused}} = \min(r_1, r_2, \ldots, r_n) \)
- **Logistic Regression:** \( s_{\text{fused}} = w_1 \cdot r_1 + w_2 \cdot r_2 + \ldots + w_n \cdot r_n \)
- **Borda Count:** \( s_{\text{fused}} = (c - r_1) + (c - r_2) \)

where \( s_i = \text{subject's score on ith candidate list}. \)
\( r_i = \text{subject's rank on ith candidate list}. \)
Multi-Finger Fusion

- Fusion using multiple fingers (not multiple impressions of the same finger).
- Two or more latent impressions are often available for a subject. For the Phase II dataset, latent images for more than one finger were available for 121 of the 588 subjects.
- For AFEM, multi-finger fusion requires little additional work on the part of the latent examiner.
Two-Finger Fusion

For the 121 subjects, two fingers were chosen randomly. The rank of the correct mate was determined for each finger.

<table>
<thead>
<tr>
<th>Rank of correct mate for first finger</th>
<th>1</th>
<th>2-10</th>
<th>11-20</th>
<th>21-50</th>
<th>Miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>86</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>12</td>
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<tr>
<td>2-10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>11-20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>21-50</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Miss</td>
<td>14</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

K1

- The correct mate was almost always:
  1) at rank one on at least one of the candidate lists.
  2) not on either candidate list.

- The Fusion method should place a high value on the rank one candidates from the unfused lists.
Two-Finger Fusion

Rank 10 identification rate.
(Gallery size 5,000; latent image resolution 500 ppi)
Multi-Algorithm Fusion

- Searching with multiple algorithms.
- Requires no additional information from the source (i.e. the subject).
- More computationally expensive.
- A smaller improvement in matching accuracy is expected due to a high level of correlation.
- It is better to combine algorithms that are less similar.
Multi-Algorithm Fusion

Pairing algorithms improves matching performance.

<table>
<thead>
<tr>
<th></th>
<th>K1</th>
<th>L1</th>
<th>M1</th>
<th>N1</th>
<th>O1</th>
<th>P1</th>
<th>Q1</th>
<th>R1</th>
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<tbody>
<tr>
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<td>.90</td>
<td>.98</td>
<td>.90</td>
<td>.94</td>
<td>.95</td>
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<td>.90</td>
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<tr>
<td>L1</td>
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<td>.83</td>
<td>.98</td>
<td>.89</td>
<td>.93</td>
<td>.94</td>
<td>.93</td>
<td>.88</td>
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<tr>
<td>M1</td>
<td>.98</td>
<td>.98</td>
<td>.97</td>
<td>.98</td>
<td>.99</td>
<td>.98</td>
<td>.98</td>
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<tr>
<td>N1</td>
<td>.90</td>
<td>.89</td>
<td>.98</td>
<td>.79</td>
<td>.92</td>
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<td>.93</td>
<td>.88</td>
</tr>
<tr>
<td>O1</td>
<td>.94</td>
<td>.93</td>
<td>.99</td>
<td>.92</td>
<td>.87</td>
<td>.96</td>
<td>.94</td>
<td>.92</td>
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<tr>
<td>P1</td>
<td>.95</td>
<td>.94</td>
<td>.98</td>
<td>.93</td>
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<tr>
<td>Q1</td>
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<td>.98</td>
<td>.93</td>
<td>.94</td>
<td>.96</td>
<td>.88</td>
<td>.92</td>
</tr>
<tr>
<td>R1</td>
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<td>.88</td>
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<td>.88</td>
<td>.92</td>
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<td>.92</td>
<td>.81</td>
</tr>
</tbody>
</table>

Rank 10 identification rate.
(Gallery size 5,000; latent image resolution 500 ppi)
Multi-Algorithm Fusion

• Highlights from Table:
  – Q1: 0.88
  – P1: 0.90
  – Q1 + P1: 0.96
  – M1: 0.97
  – M1 + O1: 0.99
Conclusions

• We see a potential for both multi-finger and multi-algorithm fusion to improve matching accuracy.
• More research to be done.
• Future methods of rank / score level fusion should use longer candidate lists.